Behaviour of Self-Compacting Reinforced Concrete with Hybrid Fibers

Synopsis of the PhD Thesis

Submitted by

Achal Agrawal

(SAP ID: 70821017001)

Department of Civil Engineering

Supervisor

Dr. Narayan R. Chandak

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MUKESH PATEL SCHOOL OF TECHNOLOGY MANAGEMENT & ENGINEERING
SVKM's NARSEE MONJEE INSTITUTE OF MANAGEMENT STUDIES (Declared as Deemed-to-be University Under Section 3 of the UGC Act, 1956)
V. L. Mehta Road, Vile Parle (West)
MUMBAI –400056

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1. Abstract

This study highlights the utilization of additives in superplasticizers, fly ash, polypropylene fibers, and carbon steel fibers to achieve the designed fresh and mechanical characteristics of Self-compacting concrete (SCC) while considering environmental sustainability. This study employs Taguchi's L18 design methodology to investigate the impact of the additives with varying levels on the rheological and mechanical properties of SCC. The research assesses both fresh properties (slump flow, V-funnel, J-ring) and hardened properties (split tensile and compressive strength at 7 and 28 days) of self-compacting concrete. Apart from conventional tests, microstructural analysis of fly ash and designed mixes are also performed wherein X-ray diffraction is utilized to classify fly ash, SEM is utilized to get microscopic insights into the arrangement and interaction of components, and EDS is utilized to quantify the elemental composition. This two-tiered approach enables a thorough grasp of the impact of regulating materials on both the macro properties and microstructure of SCC. Notably, the study reveals that fibers have a detrimental effect on SCC flow properties but a beneficial impact on hardened concrete properties. Likewise, the influence of superplasticizers outweighs that of fly ash in shaping SCC properties. Remarkably, microstructural insights align with the predictive model, highlighting the dominance of superplasticizers over fly ash. This holistic methodology bridges the gap between material composition, macro behavior, and microstructure, enriching our comprehension of SCC. It offers a robust foundation for enhancing SCC's performance across applications. Further, multiple regression analysis develops a predictive model using experimental data to understand how these components influence SCC characteristics. In addition, the study has employed predictive modelling techniques such as ANN, SVR, and MLR to predict compressive and split tensile strengths using predictive modelling. SVR was observed as the best fit model, with an IOA of 0.98 and R^2 of 0.91, for predicting compressive strength and for predicting split tensile strength; both SVR and MLR were found to give similar results.

This study has immense practical implications in the developing field of sustainable concrete technology as it aids in providing guidelines for developing high-performance SCC using sustainable materials and predictive modelling techniques. It paves the way for the construction industry to adopt more sustainable and durable concrete solutions while upholding enhanced durability and mechanical properties.

Keywords: *Self-Compacting Concrete, Rheology, Durability, Multiple Regression Model, X-Ray Diffraction, Scanning Electron Microscope, Energy Dispersion Spectroscopy, Compressive strength, Tensile strength, Support vector machines, Adaptive Neuro-Fuzzy Inference Systems with Genetic Algorithms, Artificial Neural Networks, Multiple Linear Regression*

2. Introduction

2.1 General

Concrete, the most widely used construction material globally, has exponentially accelerated the developmental rate of civilizations. It has significantly contributed to the construction industry by enhancing its properties of workability, strength, serviceability, and resistance against fire and weather [1]. It has been reported that the average use of concrete per person is around 1 m^3, thus making it the most consumed material after water on the earth's surface [2]. However, the construction process of concrete poses certain limitations from production to placement, and these limitations can be categorized based on strength, workability, durability aspects, and environmental considerations. It has been observed from the construction practices that the workability of concrete is severely affected at the places where proper placing of concrete cannot be endured, and the shortcomings lead to brittleness, resistance to flow, segregation, permeability issues, and inadequate strength-related parameters. In order to avoid such shortcomings, several techniques are adopted to develop specific types of concretes that possess characteristic features of addressing the problem [3]. Similarly, for practices where placing concrete was tedious, and vibration compaction was not feasible, a special type of concrete was developed, which is termed SCC that possesses the ability to flow and compacts under its self-weight, thus receding the requirement of external vibration compaction [4], [5].

SCC is generally suitable for heavily reinforced structures where passing spaces between the reinforcing bars are less, and the vibration is complex to compact the concrete. In addition, it is advantageous in severe environments wherein exposure time is reduced to its property of self-compaction. Further, some of its advantages include minimization of noise pollution by eliminating vibration, reduction of excess labour, enhancement in durability, and enhancement in strength [6].

2.2 Research Problem

SCC, a specialized construction material, necessitates watchful consideration due to inherent challenges posed by conventional concrete constituents, viz. cement, sand, and coarse aggregates. Predominantly, SCC contends with issues in flowability, delayed strength development, segregation, and durability. To address these challenges, a specialized mix is requisite, involving the judicious incorporation of various materials, including superplasticizers, fly ash, and fibers, in varying proportions. These elements collectively aim to optimize rheological characteristics, mechanical properties, and durability aspects.

In the aspect of sustainability and waste utilization, the utilization of fly ash becomes of pivotal focus. Given its mineralogical composition and pertinent research findings, the material presents a substantial opportunity for integration into concrete matrices. Novel SCC mixes, leveraging innovative additives, are thus formulated and subjected to rigorous analysis to ascertain their efficacy in meeting SCC requirements while ensuring sustainable practices.

In addition, computational approach seeks to streamline the development process, minimizing the need for extensive experimental trials and enhancing precision in design optimization. The study addresses the multifaceted challenge of enhancing concrete's mechanical properties. Conventional formulations often grapple with inadequacies in tensile strength, ductility, and resistance to cracks, prompting a need for advanced solutions.

2.3 Research Significance

The current study focuses on the sustainability of SCC while highlighting its importance, utilization, and optimization. The study incorporates the usage of additives in the form of superplasticizers, fly ash, polypropylene fibers, and carbon steel fibers to achieve the designed fresh and mechanical characteristics of SCC while taking environmental sustainability into consideration. The study utilizes the Taguchi method for the design of the experiment, and the L-18 design is adopted to minimize the experimentation with reliable results. Several tests, such as fresh concrete property tests, strength tests, and durability tests, have been performed on all the designed mixes of SCC, and their characteristics have been highlighted for designated utilization.

This study further examines the microstructural composition of fly ash and fly ash-based self-compacting concrete using X-ray diffraction, scanning electron microscope, and energy dispersive spectroscopy to understand material composition. Further, the microstructural analysis aids in assessment of homogeneity in mix after hardening, detection of air voids, assessment of un-hydrated cement particles, evaluation of undesirable reactions that may impact performance, optimizing mix design, and maintenance of quality control during production. Based on the beneficial factors of microstructural analysis, the utilization of microstructural analysis plays a pivotal in determining its strength, durability, and resistance to environmental degradation. Further, it aids in understanding the role of additives in altering the microstructural composition of concrete, that gets crucial in harnessing the material's full potential.

The study further aids in providing a numerical model developed using eight multiple regression models built using the statistical package Minitab to analyse the performance of designed concrete based on the four key parameters. The numerical tools were trained and validated for the results obtained from the experimental analysis.

The findings presented in this study and the numerical model developed significantly contribute to the broader body of knowledge on alternative construction materials, hence aiming to guide the construction industry towards eco-friendlier and high-performance solutions.

3. Objectives

1. To study the feasibility of hybrid fibers (synthetic and steel) on fresh concrete properties of self-compacting concrete.
2. To evaluate the mechanical properties of Hybrid Fiber Self-Compacting Reinforced Concrete (HYSCRC) and find the optimum dosage of hybrid fibers.
3. To examine the durability parameters of HFSCRC.
4. To examine the microstructural characteristics of HFSCRC.
5. To develop numerical models for the behavioral characteristics of HFSCRC.

4. Literature Review

4.1 Material selection for SCC

Table 1 shows a variety of material used by the researchers in their study, which gives a better understanding of different combination and effects of proportions on the behaviour of SCC. A detailed review of approximately 250 mixes is done in this study where 22 case studies are reported. The study describes the type of superplasticizers used to achieve the required consistency in terms of SCC. It gives details about the cement type, mineral admixtures used, fine and coarse aggregates used along with the type of fibers utilized for the studies.

Table 1. Database for mix design of SCC with hybrid fibers

Reference	Year	Superplasticizer Type	Material Used				Fibers used
			Fine Aggregates	Coarse Aggregates	Cement	Mineral admixtures	
[7]	2019	Polycarboxylate based SP	Natural River Sand	Crushed expanded shale ceramist	OPC 42.5N	Fly ash and Silica Fumes	Straight Steel & Polypropylene
[8]	2017	Polycarboxylate based SP	Natural River Sand	Coarse Aggregates	CEM I 42.5R	-	Straight steel & Corrugated Steel
[9]	2019	High Range Water Reducer	Fine aggregates	Coarse Aggregates	Portland Cement	Silica Fumes	Hooked end Steel & Crimped Steel
[10]	2016	Glenium Sky 504	Crushed Sand < 4.75 mm and Dune Sand < 0.3 mm	Crushed Limestone < 10 mm	OPC	Silica Fumes	Steel Fiber & Synthetic Fiber
[11]	2017	Polycarboxylate based	Sand	Coarse Aggregates	OPC type II	Silica Fumes and Limestone Powder	Hooked End Steel & PP Fiber
[12]	2018	Glenium 51	Natural River Sand	Coarse Aggregates < 9.5 mm	OPC Type III	Fly ash and Silica Fumes	Hooked End Steel & PP Fiber
[13]	2019	Poly-carboxylate Ether (PCE) Polymer	Fine River Sand < 2.4 mm Coarse River Sand < 4.8 mm	Crushed Granite type-I Crushed Granite type-I	Cem I (42.5 R)	Fly ash	Hooked Steel Fiber
[14]	2020	Sika Viscoconcrete	Karbala Sand	Natural Coarse and Light Expanded Clay Aggregates	Portland Cement	Limestone Powder	Micro Steel Fibers
[15]	2018	Polycarboxylic ether	River Sand	Crushed Granite Aggregates	Portland Cement (Type-II)	Fly ash	Steel Fiber & Polypropylene Fibers
[16]	2020	Polycarboxylate Ether	Natural River Sand (0-2 mm)	Lightweight Expanded Clay Aggregates	Portland Cement CEM-I (52.5 N)	Limestone Powder	Micropolypropylene & Macropolypropylene fiber
[17]	2020	High Range Water Reducer	Natural Sand	Rounded Gravel < 10 mm	Portland Cement Type-I	Limestone Powder	Wood, Polyvinyl Chloride, Aluminium Fiber

							& Iron Fillings
[18]	2019	High Range Water Reducer	Natural River Sand < 5 mm	Coarse Aggregates < 10 mm	OPC Type-I	Micro Silica	Polyethylene terephthalate
[19]	2018	Polycarboxylic ether	Natural Sand and Crushed Sand	Crushed Limestone	CEM 42.5R	Silica Fumes and Metakaolin (MK)	Hooked-end Steel Fibers
[20]	2018	Varaplast PC 432	Sand (0-2 mm)	Angular Aggregates (8-16 mm)	OPC (53 Grade)	Class F Fly Ash	Steel, Sisal & Abaca
[21]	2020	High Range Water Reducer	Fine Silica Sand, Natural Aggregates and Magnetite Fine Aggregates	Natural Aggregates and Magnetite Aggregates	General Purpose Cement (GPC)	Grade-I Fly ash, Ground Granulated Blast Furnace Slag and SF	Steel Fiber & Polypropylene Fibers
[22]	2020	Aura mix 300	Normal Sand or Squashed Stone < 5 mm	Aggregates < 12.5 mm	OPC	-	Steel Fiber & Nylon Fiber
[23]	2020	Polycarboxylic based super lubricant	Round Corner Sand	Coarse Broken Grains	325-1 type Portland	Silica Fumes	Basalt Fiber
[24]	2020	Superplasticizer	River Sand	Crushed Limestone	Portland Cement	Stone Powder	Hooked Steel Fiber
[25]	2020	Sika ViscoCrete-5930	Sand	Local Siliceous Gravel	Portland Cement	Lime Stone Powder	Micro Steel Fiber
[26]	2020	Superplasticizer	Sand	Natural Coarse Aggregates	OPC I (42.5)	Lime Stone Powder and Fly ash	Steel Fiber
[27]	2019	SP	Sand < 5 mm	Gravel < 16 mm	Portland Cement CEM I	Nano Silica and FA	Glass Fiber
[28]	2019	Salt of a polymeric naphthalene sulphonate Daracem	River Sand	Rounded Aggregates < 10 mm	Portland Cement CEM I (42.5R)	Fly ash	Hooked end Steel Fiber

4.2 Effect of constituents on fresh and mechanical properties of SCC

Citing the characteristics of SCC, it is a pre-requisite for the SCC to have better flowability with volumes of 8-10% coarser particles as compared to concrete [29, 30], and this limitation creates a sense of hesitancy regarding the use of SCC, especially wherein high strength characteristics and avoidance of segregation of concrete are required. Henceforth, an alternative has been suggested in the form of the addition of fibers in the SCC, wherein fibers are known for playing an important role in providing resistance to flow and enhancing the ductility in the SCC, thus making it more suitable to bear the tensile loads [31]. In recent times, numerous studies have been carried out that are focused on the application of different types of fibers in concrete, hence enhancing the flexural properties of concrete. Sherif Yehia et al. 2016 [32] studied the effect of fibers on the mechanical and durability properties of

SCC and concluded that the addition of fibers efficiently aids in the enhancement of the mechanical and durability properties of SCC. Ángel de la Rosa et al. [33] suggested the importance of mixing in SCC and hence proposed a novel mixing method for SCC and observed compressive strength of 30 MPa to 80 MPa, thus emphasizing the utilization of SCC for the production of high- strength concrete. The influence of fibers on the workability properties of SCC is investigated by many researchers [34], [35], [36], [37], and their findings suggested that the fibers have decreased the workability properties of SCC but aided help in enhancing the mechanical properties of SCC. R. Prakash et al. 2021 [38] stated that the mechanical characteristics of SCC significantly increased by adding Roselle fibers. Through the experimental placement of SCC, it was also determined that the inclusion of fibers results in a reduction in workability, and to address this challenge, a recommended solution involves incorporating superplasticizers at proportions of 1.5% to 2.0%, Which is crucial to attaining the necessary workability for the concrete mixture. K.M.A. Hossain et al. 2020 [39] concluded that the ductile properties of SCC can be enhanced by adding fibers to it. Further, numerous studies were conducted to evaluate the workability and compressive strength of concrete, and it was suggested that in order to achieve the desired workability without compromising with strength, superplasticizers and viscosity modifiers should be used [40], [41], [42].. Further, multiple studies were conducted to elaborate on the importance of mineral admixtures for the attainment of perfectly designed SCC. It was concluded that ordinary Portland cement should be generally used with different proportions of mineral admixtures to have a higher volume of fines [43], [44].

4.3 Durability and microstructural properties of SCC

Ramanathan P. et. al. 2013 [45] deduced that using higher volume of powder content in the form of cement and mineral admixture in the SCC reduces the coarse aggregate content and improves durability, thus making it suitable for use in the design of SCC. Apart from the conventional methods of testing for fresh properties, mechanical characteristics, and durability characteristics obtained using different standards of practice, a relatively novel practice has been suggested in the form of microstructural analysis to evaluate the post-curing structure and bond formations in SCC [46]. Gritsada Sua-iam et al. 2024 [47] stated that fly ash [48], in addition to silica fumes and recycled coarse aggregates, alters the pattern and rate of chloride ion movement in SCC and alters SCC's durability. Including copper slag into SCC enhances its durability, as it reduces water absorption and chloride penetration [49]. Hadi H. Edan et al. 2023 [50] concluded that using walnut shell particles as fine aggregates improves the mechanical properties and durability of SCC. In addition, by adding hybrid fibers of steel and polypropylene, crack resistance is increased, resulting in improved structural integrity and durability [51]. Microstructural analysis that consists of an X-ray diffraction technique, scanning electron microscope, and energy dispersion spectroscopy has been employed during the current study to investigate the elemental composition, bond formation, and different compound formations in the fly ash and SCC. Microstructural analysis reveals the matrix structure, as investigated by Hemn Unis Ahmed et al. 2023 [52], geopolymer concrete with nano silica depicted dense and compact matrix in the SEM images, contributing to concrete's improved mechanical and durability characteristics. Microstructural analysis also aids in assessing the effect of additives on the strength parameters such as compressive strength, modulus of elasticity and tensile strength of SCC [53].

4.4 Numerical modeling used for prediction of various parameters of SCC

Numerical techniques have proven to be a beneficial tool in designing concrete with precision and saving human time and effort. Henceforth, numerous efforts have been made to evaluate different concrete characteristics using different techniques. Chithra, Sarangapani, et al. 2016 [54] developed a multiple linear regression model (MLR) model along with advanced neural network (ANN) techniques to predict the compressive strength of concrete. The determination coefficient from the Durbin–Watson test was observed to be very low. The test for multi-collinearity in the MLR model was not satisfied, and to optimize the test exercise of concrete, which is self-compacting, Selvaraj, Sundari, et al. 2019 [55] applied the IREMSVM-FR technique thus built a model for predictive model for determination of properties on concrete and using response surface methodology satisfactorily optimized the maximum slump flow and compressive strength. Feng, Lu, et al. 2021 [56] analyzed the features of SCC and developed a model that can be applied to determine the amplitude and incremental testing methodology. Teixeira S. et al. 2016 [57] developed a numerical model that could be used to estimate the lateral pressure exerted by self-compacting concrete. Adesanya, Elijah, et al. 2021 [58] developed an ANN algorithm to determine the drying shrinkage of alkali-activated blast furnace fly ash mortars. Bui, Dac-Khuong, et al. 2018 [59] modified an ANN algorithm to maximize and improve the efficiency of weights and biases. Ahmad Alyaseen et al. 2024 [60], utilized statistical techniques and machine learning to assess the splitting tensile and compressive strength of SCC, and these techniques were found to be feasible in predicting the strength parameters of SCC. Swamy Naga Ratna Giri Pallapothu et al. 2023 [61] suggested that machine learning models can promisingly assess the strength of SCC and reduce the need for extensive laboratory testing, saving time and cost.

Advanced machine learning algorithms and computational models are used as an AI technique to predict the strength of SCC. These methods create intricate connections between input variables and the compressive strength of SCC by utilizing the power of data-driven analysis. The composition of cement, fly ash, ground granulated blast furnace slag, water-to-binder ratio, superplasticizer dosage, and the presence of fibers may all be important factors in predicting SCC strength [62, 63]. ANNs, modeled after the human brain's neural connections, are one widely used AI technique. ANNs can successfully handle nonlinear relationships and capture the intricate interactions between input parameters and SCC strength [62, 63]. Support Vector Regression (SVR), which excels at managing complex data distributions and delivering trustworthy results, is another AI technique used in SCC strength prediction [64]. Additionally, a versatile AI method called genetic programming (GP) is used to develop mathematical expressions that simulate the relationship between input parameters and SCC strength [65]. GP uses evolutionary algorithms to iteratively improve mathematical models, improving the predictions based on experimental and historical data. There are several benefits to using AI methods to predict SCC strength. First, it speeds up the mix design procedure and eliminates the need for time-consuming, expensive experimental trials. Second, AI models can easily handle sizable datasets, incorporating various parameters that influence SCC strength, resulting in thorough analysis and more precise predictions [66]. Additionally, careful selection of the AI technique and appropriate parameterization is crucial to avoid overfitting or underfitting the data [66, 67]. Pallapothu et al. [68] suggested that particle packing models and machine learning may be used to estimate and optimize the packing density of the concrete mixture. Further, data obtained through the estimation was used as input in a machine-learning model. The findings suggested that the developed method performs better than conventional empirical models in precisely forecasting the compressive strength of concrete based on packing density and does away with the necessity for experimenting with various mix proportions.

5. Contribution

5.1 Experimental design and casting

In this study, Taguchi's methodology [69] was employed to design experiments, explicitly focusing on SCC formulation. The design process for SCC involves using multiple materials and numerous trials typically required to achieve the desired fresh concrete properties, as shown in fig. 1. To streamline and minimize the number of trials, an L18 Taguchi's array was employed, incorporating two-level factors for superplasticizer and three-level factors for fly ash, steel fibers, and polypropylene fibers, as described in Table 2. The mixed design by weight for SCC that is derived after several trials with varying quantities of materials is presented in Table 3. The mix design criteria employed during the study optimizes the number of trials to be carried out for SCC preparation wherein different combinations for design mix have been enlisted. Further, the critical aspect termed the mixing process, follows a staging approach as recommended by Sambangi, A., & Eluru, A.(2022) [49], wherein alternate mixing and resting intervals are requisite for the preparation of the final mix as described in Fig. 2. This systematic experimental design has aided in comprehensive investigation of the factors influencing SCC properties while optimizing efficiency by reducing the number of required trials.

Table 2 Level Distinction of Taguchi's for Array Method

Level	Superplasticizer (%)	Fly Ash (kg/m^3)	Carbon Steel Fiber (%)	PP Fiber (%)
1	1.5	115	0	0
2	2	130	0.5	0.25
3	-	145	1	0.50

Table 3 Taguchi's array of design mix by weight for SCC preparation

Mix	Superplasticizer (%)	Fly Ash (kgs)	PP Fiber (%)	Steel Fiber (%)	Cement (kgs)	w/p Ratio	Fine Aggregates (kgs)	Coarse Aggregates (kgs)		Water (Kgs)	Flyash + Cement Content (kgs)	SP (kgs)	PP Fiber (kgs)	Steel Fiber (kgs)
								12.5-10 mm	10-4.75 mm					
M-01	1.5	115	0	0	485	0.4	810	365	365	240	600	9	0	0
M-02	1.5	115	0.25	0.5	485	0.4	810	365	365	240	600	9	1.5	3
M-03	1.5	115	0.5	1	485	0.4	810	365	365	240	600	9	3	6
M-04	1.5	130	0	0	485	0.4	810	365	365	246	615	9.225	0	0
M-05	1.5	130	0.25	0.5	485	0.4	810	365	365	246	615	9.225	1.535	3.07
M-06	1.5	130	0.5	1	485	0.4	810	365	365	246	615	9.225	3.07	6.15
M-07	1.5	145	0	0.5	485	0.4	810	365	365	252	630	9.45	0	3.15
M-08	1.5	145	0.25	1	485	0.4	810	365	365	252	630	9.45	1.575	6.3
M-09	1.5	145	0.5	0	485	0.4	810	365	365	252	630	9.45	3.15	0
M-10	2	115	0	1	485	0.4	810	365	365	240	600	12	0	6
M-11	2	115	0.25	0	485	0.4	810	365	365	240	600	12	1.5	0
M-12	2	115	0.5	0.5	485	0.4	810	365	365	240	600	12	3	3
M-13	2	130	0	0.5	485	0.4	810	365	365	246	615	12.3	0	3.07
M-14	2	130	0.25	1	485	0.4	810	365	365	246	615	12.3	1.535	6.15
M-15	2	130	0.5	0	485	0.4	810	365	365	246	615	12.3	3.07	0
M-16	2	145	0	1	485	0.4	810	365	365	252	630	12.6	0	6.3
M-17	2	145	0.25	0	485	0.4	810	365	365	252	630	12.6	1.575	0
M-18	2	145	0.5	0.5	485	0.4	810	365	365	252	630	12.6	3.15	3.15

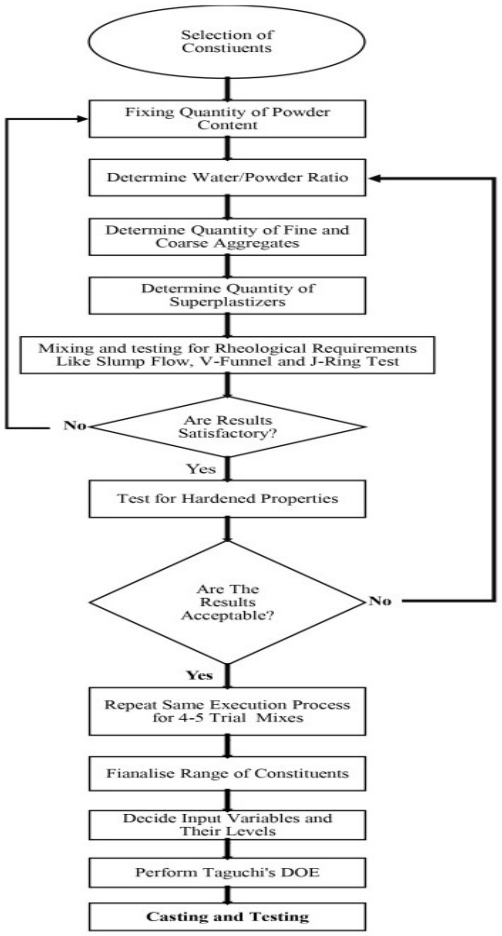
Selection of Constiuents
Fixing Quantity of Powder Content
Determine Water/Powder Ratio
Determine Quantity of Fine and Coarse Aggregates
Determine Quantity of Superplastizers
Mixing and testing for Rheological Requirements Like Slump Flow, V-Funnel and J-Ring Test
No
Are Results Satisfactory?
Yes
Test for Hardened Properties
Are The Results Acceptable?
No
Yes
Repeat Same Execution Process for 4-5 Trial Mixes
Fianalise Range of Constituents
Decide Input Variables and Their Levels
Perform Taguchi's DOE
Casting and Testing

Fig. 1 Experimental procedure flowchart

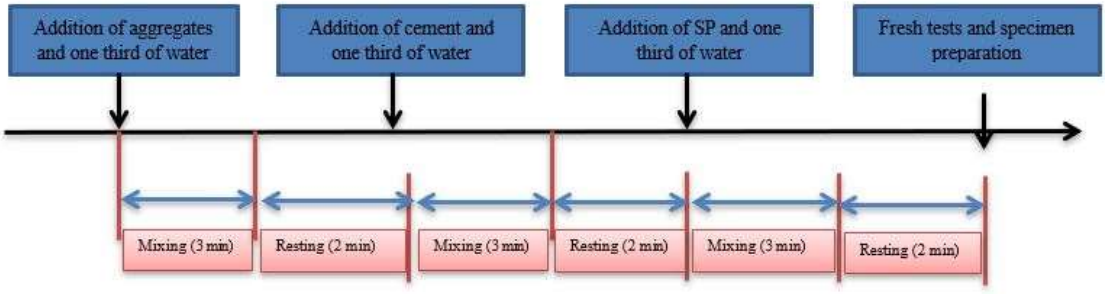
Addition of aggregates and one third of water
Addition of cement and one third of water
Addition of SP and one third of water
Fresh tests and specimen preparation
Mixing (3 min)
Resting (2 min)
Mixing (3 min)
Resting (2 min)
Mixing (3 min)
Resting (2 min)

Fig. 2 Description of mixing approach [69]

5.2 Fresh Properties of SCC

Fresh properties of SCC encompass the set of properties such as workability, segregation resistance, bleeding, and permeability, which are investigated for fresh SCC. The European Federation of National Associations Representing for Concrete (EFNARC 2002, 2005) [29], [30], issued a set of guidelines to ensure the workability and flowability of SCC. EFNARC suggested a limiting range for several tests carried over SCC that includes slump flow (mm), slump flow (sec), J-ring (step height), and V-funnel (sec).

The suggested tests were performed over freshly prepared SCC following the EFNARC guidelines to check different workability aspects of SCC. Slump flow test ranges were suggested to be in the range of 600-800 mm for better flowability/ filling ability of SCC and avoidance of segregation, and it was observed that the slump flow test results for all the mixes were coherent and lay in the suggested range as depicted in Fig. 3 and Table 4. Further, to ensure the consistency of flow or its filling ability, the time duration (T50cm) recommended to record the flow of 50 cm is 2-5 seconds, and it was observed that desired values were obtained in maximum mixes. However, an enhanced time interval was observed for M3. A reduced time interval was observed for M4 and M16, attributed to the highest percentage of hybrid fibers and the lower percentage of hybrid fibers, respectively, as described in Table 4. In addition, for the SCC passing test, the J-ring test was suggested with the range of step height 0-10 mm as depicted in Fig. 4. It was observed that all the mixes were in accordance with the designated standards, having specified passing ability as described in Table 8. Further, for segregation resistance, V-funnel flow is recommended wherein the typical flow range is 6-12 s, and it was observed that overall flow was in similitude with the recommendations with higher resistance observed in M2 and M3, which is attributed to the presence of hybrid fibers, in the freshly prepared SCC.

Fig. 3 Slump flow test

Fig. 4 J-ring measurement

Table 4 Workability test

Mix no.	Slump flow (mm)	Slump flow (sec)	V-funnel (sec)	J-ring (mm)
M-1	780	2	7	0.5
M-2	665	5	13	1.2
M-3	630	6	14	1.9
M-4	790	1.5	6	0.2
M-5	730	3	9	1
M-6	690	4	11	1.5
M-7	750	2.5	8	0.8
M-8	730	3	8	1

M-9	725	3	9	1
M-10	760	2	8	0.7
M-11	765	2	7	0.6
M-12	710	4	12	0.8
M-13	775	2	7	0.3
M-14	725	3	9	0.5
M-15	710	4	10	1.1
M-16	800	1	6	0
M-17	785	2	6	0.2
M-18	750	3	9	0.4

5.3 Mechanical Properties

Mechanical properties or strength characteristics are defined as the material's ability to resist or support different forces acting along different lines of action. Investigation of the strength properties of SCC is of paramount importance considering the fact of construction utility purposes. Some of the key indicators of strength parameters are compressive strength and tensile strength, wherein the compressive strength characteristics are studied for the determination of the ability to bear axial loads that are essential for ascertaining the structure's load-bearing capacity. Further, Split tensile strength parameters are determined to ascertain the tensile strength of concrete that otherwise proves to be a weak link when subjected to tensile loads. During the current study, SCC was tested for split tensile strength and compressive strength to determine the effect of the strength parameters of concrete on the addition of fiber and fly ash additives. The tests during the study were performed in accordance with IS-516:1959 [70] and IS-5816:1999 [71] for compressive strength and splitting tensile strength, respectively. Further, the tests were carried out on curing periods of 7 days and 28 days, respectively, thus evaluating the effect on strength characteristics of the designed SCC as depicted in Fig. 5. It was observed that for the design mix, M18 peak, compressive strength after seven days and 28 days curing was highest amongst all the mixes with compressive strength values of 40.2 MPa and 57.2 MPa respectively as given. Consequently, the minor compressive strength parameters were obtained for the design mix M1 amongst all the mixes with compressive strength values of 24.1 MPa and 36.1 MPa after the seven and 28-day curing, respectively. Furthermore, a Similar trend is observed in the split tensile strength of SCC, as depicted in Fig. 6

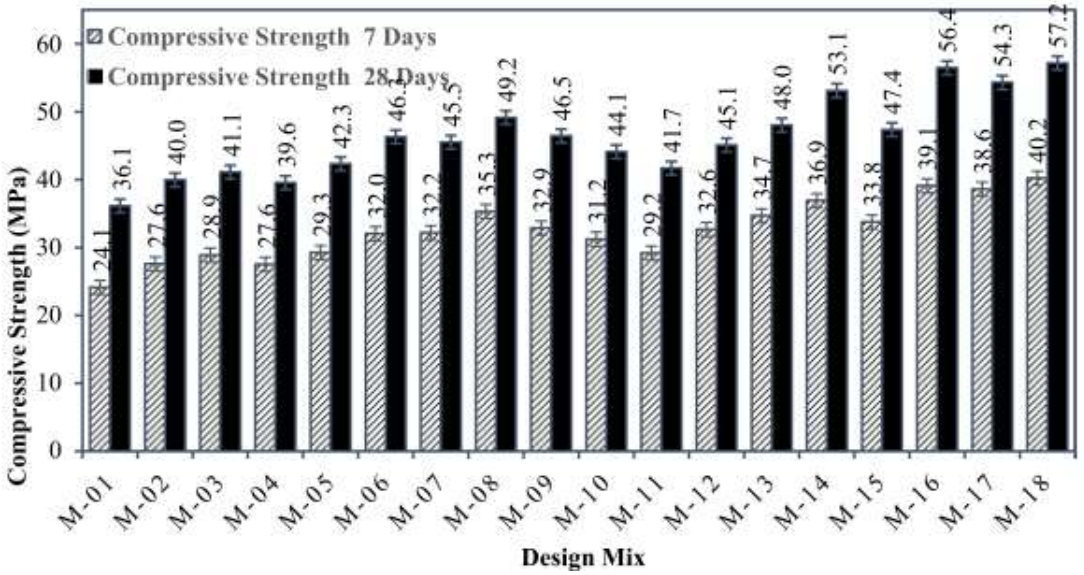

Fig. 5 Compressive strength of SCC

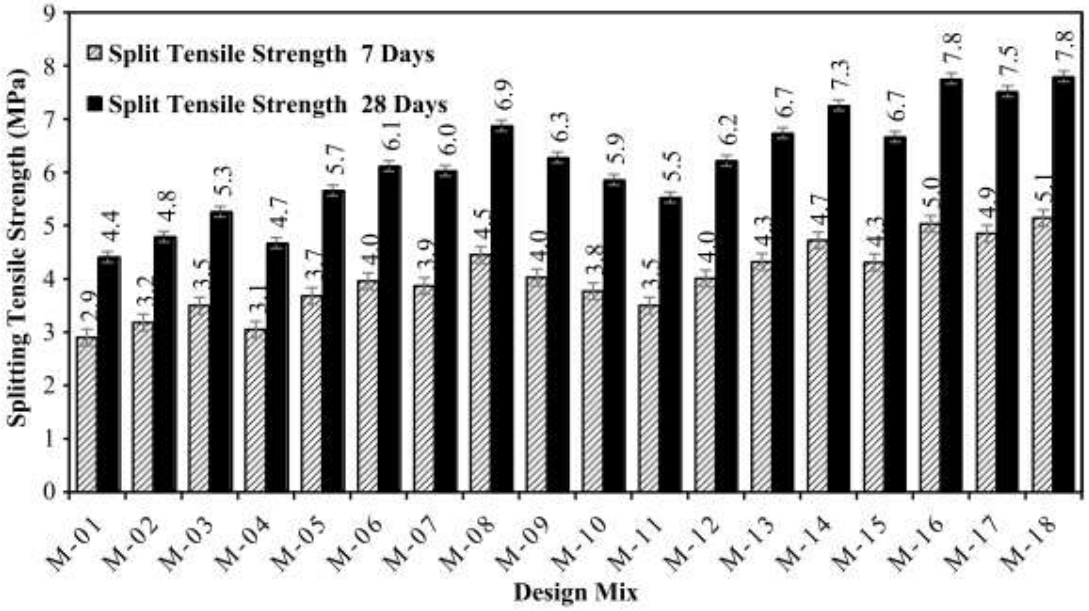

Fig. 6 Split tensile strength of SCC

5.4 Durability Properties

In the perspective of materials like SCC, durability may be referred as the ability of the concrete or the structure constructed using it to withstand environmental or operational factors over an extended period without any substantial deterioration. For concrete specifically, durability studies are considered very crucial, aiding the fact the structures are susceptible to undergo numerous potentially catastrophic conditions. It is proposed that durable concrete shall maintain the intended function, strength, and appearance despite exposure to environmental conditions such as weathering, chemical attacks, abrasion, and other forms of wear and tear. Several vital aspects are suggested as per Indian standards to check the durability conditions of concrete, which primarily involves permeability evaluation

that is determined using sorptivity characteristics and absorption tests [72]. Permeability tests are performed to resist the ingress of water, which are evaluated to protect the steel from corrosion and ensure the structure's longevity. It was observed that maximum sorptivity was observed to be 10.133 × 10-3 cm/min1/2 for M1 and the least value of 7.941 × 10-3 cm/min1/2 for M18 as given in Table 5, which construes the fact that addition of fibers and fly ash aids in decreasing the sorption characteristics thus enhancing the durability characteristics of designed SCC.

Furthermore, water absorption was also performed as per guidelines suggested by ASTM Standard, C-1585-04 (2004) [73]. It was observed that the highest initial water absorption was 2.01 % for M-1. Minor absorption was recorded at 1.04 % in M-18, maximum saturated water absorption at 10.133% in M1, and minimum saturated water absorption at 5.86 % in M-18, as given in Table 6. It was further inferred from water absorption results that adding fibers and fly ash considerably aids in the increase of durability characteristics of SCC. In addition, an important test termed the chloride penetration test, mainly used for marine environments and coastal structures, was performed as per the guidelines suggested [74], and this evaluation is crucial for evaluating the penetration depth of chloride ions that may, in turn, cause the corrosion in reinforcement. In addition, the chloride penetration test is used to evaluate durability assessment, service life prediction, quality control, and consideration of specific environmental conditions and exposure risks. It was further observed that maximum chloride penetration was recorded for M-1 with a penetration depth of 0.0285 m and diffusion coefficient of 1.679 × 10-11 and for M-18 with a penetration depth of 0.02 m and diffusion coefficient of 0.827 × 10-11 as given in Table 7. Further, it may be inferred from the chloride penetration that for corrosion characteristics in particular and durability characteristics in general, the modified design mix involving fly ash and hybrid fibers is sustainable and durable for designing SCC.

Table 5 Sorptivity characteristics of SCC

Mix	Weight of Water Penetration in Grams (g) after Immersing in Water for		Volume of Water Penetrated/Surface Area of Exposure (cm)		Sorptivity (cm/min^0.5) 10^-3
	30 min	120 min	30 min	120 min	
M-01	22.73	44.36	0.101	0.197	10.133
M-02	21.64	42.26	0.096	0.188	9.660
M-03	21.57	41.56	0.096	0.185	9.365
M-04	21.53	42.58	0.096	0.189	9.861
M-05	21.44	41.53	0.095	0.185	9.412
M-06	21.12	40.73	0.094	0.181	9.187
M-07	20.87	39.54	0.093	0.176	8.746
M-08	20.82	38.86	0.093	0.173	8.451
M-09	21.03	39.63	0.093	0.176	8.714
M-10	22.52	41.58	0.100	0.185	8.929
M-11	22.68	42.01	0.101	0.187	9.056
M-12	22.41	41.18	0.100	0.183	8.793
M-13	21.61	40.12	0.096	0.178	8.672
M-14	20.85	38.75	0.093	0.172	8.386
M-15	21.13	39.18	0.094	0.174	8.456
M-16	20.59	38.17	0.092	0.170	8.236
M-17	20.89	38.98	0.093	0.173	8.475
M-18	20.13	37.08	0.089	0.165	7.941

Table 6 Water absorption characteristics of SCC

Mix	Weight W1 (kg)	Weight W2 (kg)	Initial Water Absorption (%)	Weight W3 (kg)	Saturated Water Absorption (%)
M-01	8.731	8.914	2.10	9.558	9.47
M-02	8.694	8.861	1.92	9.485	9.10
M-03	8.762	8.915	1.75	9.500	8.42
M-04	8.667	8.836	1.95	9.468	9.24
M-05	8.715	8.870	1.78	9.446	8.39
M-06	8.798	8.941	1.62	9.516	8.16
M-07	8.263	8.385	1.48	8.915	7.89
M-08	8.316	8.422	1.27	8.891	6.91
M-09	8.116	8.233	1.44	8.743	7.73
M-10	8.803	8.939	1.54	9.523	8.18
M-11	8.684	8.821	1.58	9.413	8.39
M-12	8.719	8.847	1.47	9.410	7.93
M-13	8.628	8.748	1.39	9.267	7.41
M-14	8.775	8.881	1.21	9.366	6.74
M-15	8.593	8.702	1.27	9.207	7.15
M-16	8.615	8.713	1.14	9.179	6.55
M-17	8.216	8.315	1.20	8.764	6.67
M-18	8.367	8.454	1.04	8.857	5.86

Table 7 Chloride penetration characteristics of SCC

Mix	Depth of Chloride Penetration in m	Diffusion Coefficient in 10^{-11} m^2/sec
M-01	0.0285	1.679
M-02	0.0275	1.563
M-03	0.0260	1.397
M-04	0.0280	1.620
M-05	0.0255	1.344
M-06	0.0250	1.292
M-07	0.0235	1.141
M-08	0.0225	1.046
M-09	0.0230	1.093
M-10	0.0245	1.241
M-11	0.0250	1.292
M-12	0.0225	1.046
M-13	0.0220	1.000
M-14	0.0210	0.911
M-15	0.0215	0.955
M-16	0.0210	0.911
M-17	0.0210	0.911
M-18	0.0200	0.827

5.5 Microstructural Analysis Using Scanning Electron Microscope and Energy Dispersive Spectroscopy

Microstructural analysis, which involves the qualitative analysis and quantification of the composition of material at the micro level, plays a critical role in understanding the properties and performance of self-compacting concrete. The microstructural analysis carried out during the study, which includes Scanning Electron Microscope (SEM) and Energy dispersion spectroscopy (EDS), has aided in obtaining the elemental composition of SCC composite, packing efficiency of materials, geometry assessment of particles, understanding homogeneity, assessing particle packing and identifying segregation and bleeding. SEM aids in visualizing the cement matrix, constituents of SCC composite, and geometry of elements, as shown in Fig. 7-10.

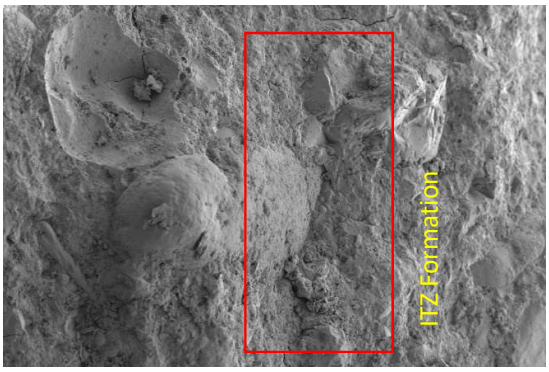

Fig. 7 ITZ Formation

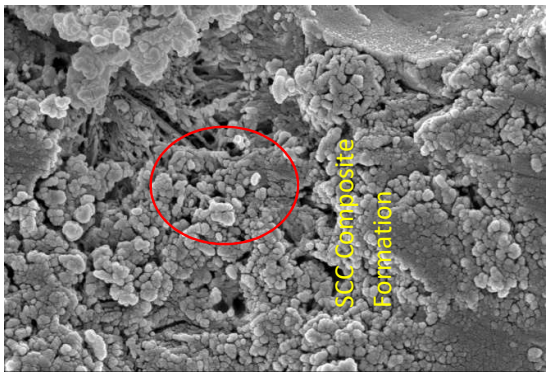

Fig. 8 SCC Composite formation

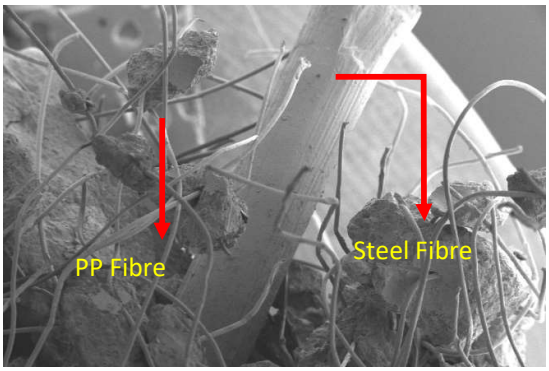

Fig. 9 Hybrid fibres

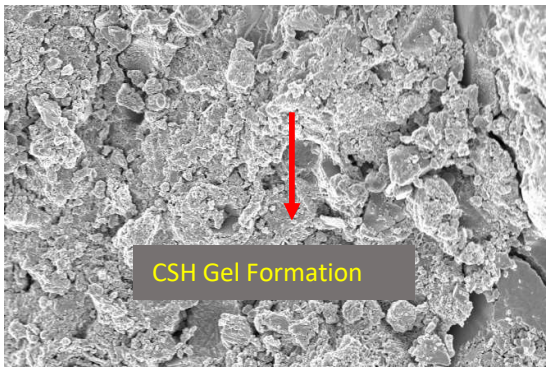

Fig. 10 CSH gel formation

EDS is an analytical technique associated with SEM that aids in identification and quantification of composition of material. It acts as a valuable tool for determination of elemental composition of sample. It is typically integrated with scanning electron microscopy (SEM) or transmission electron microscopy (TEM) systems to provide information about the chemical composition of materials at a microscale or nanoscale level. EDS is a valuable tool for both qualitative and quantitative elemental analysis. By combining SEM, and EDS techniques for the microstructure analysis of concrete a comprehensive understanding of a material's microstructure that includes surface morphology, defects, and phase distribution. A typical EDS analysis of Design Mix M1 that is composed fly ash, cement, coarse aggregates, fine aggregates, and super plasticizer has revealed the existence of Oxygen (44.3%), Carbon (16.7%), Calcium (17.5%) Silicon (6.7%) and others as indicated in Fig. 11 and Fig. 12 and Table 8. Furthermore, the analysis establishes the presence of basic concrete components present in the material [75], [76].

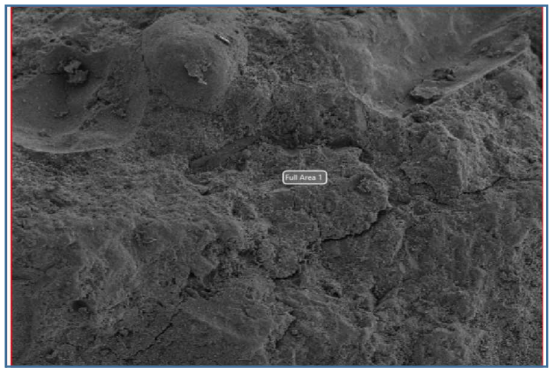

Fig. 11 EDS of M1

Table 8 Elemental composition M1 (%)

Element	Weight %
C	16.7
N	3.9
O	44.3
Mg	0.3
Al	1.7
Si	6.7
S	6.8
K	0.4
Ca	17.5
Fe	1.7

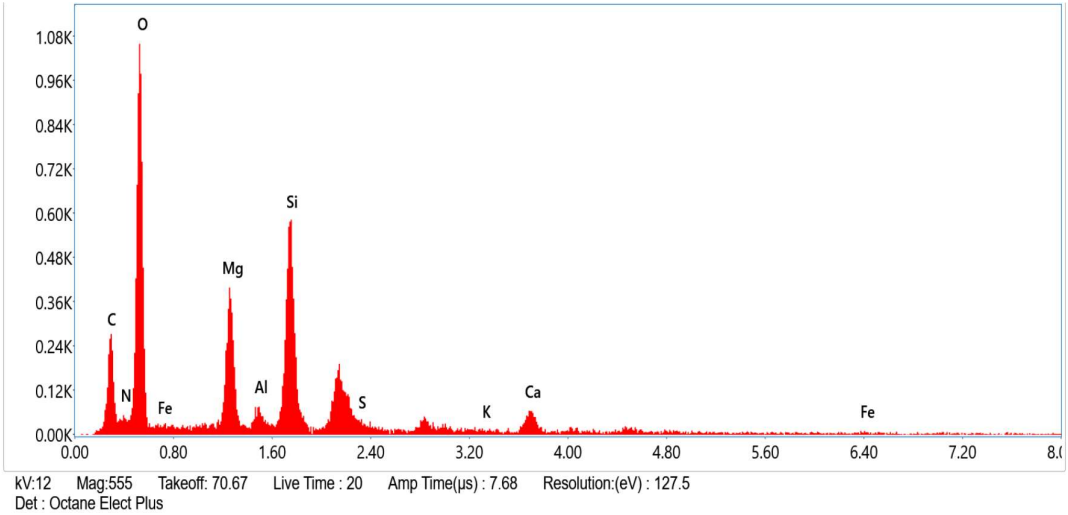

Fig. 12 Elemental analysis of SCC mix M1

In addition to M1 the design mix M18 that composes of fly ash, cement, coarse aggregate, fine aggregate and steel fibers as depicted in Fig. 13 and Fig. 14 and Table 9 has shown the presence of carbon, oxygen, silicon is usual percentage but an enhance in the presence of Iron and Aluminium has also been observed that indicates the presence of steel fibers in the sample.

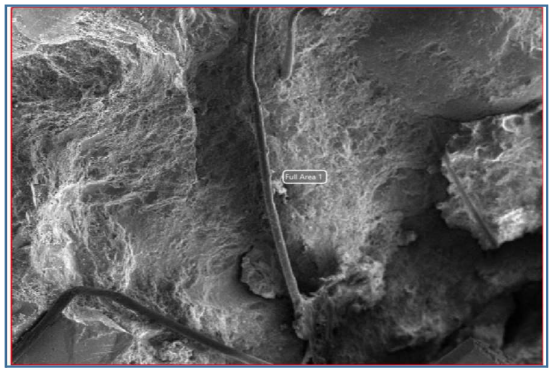

Fig. 13 EDS of M18

Table 9 Elemental composition M18 (%)

Element	Weight %
C	20.7
N	1.5
O	37.1
Mg	0.3
Al	1.9
Si	8.1
S	5.4
K	0.4
Ca	20.8
Fe	3.8

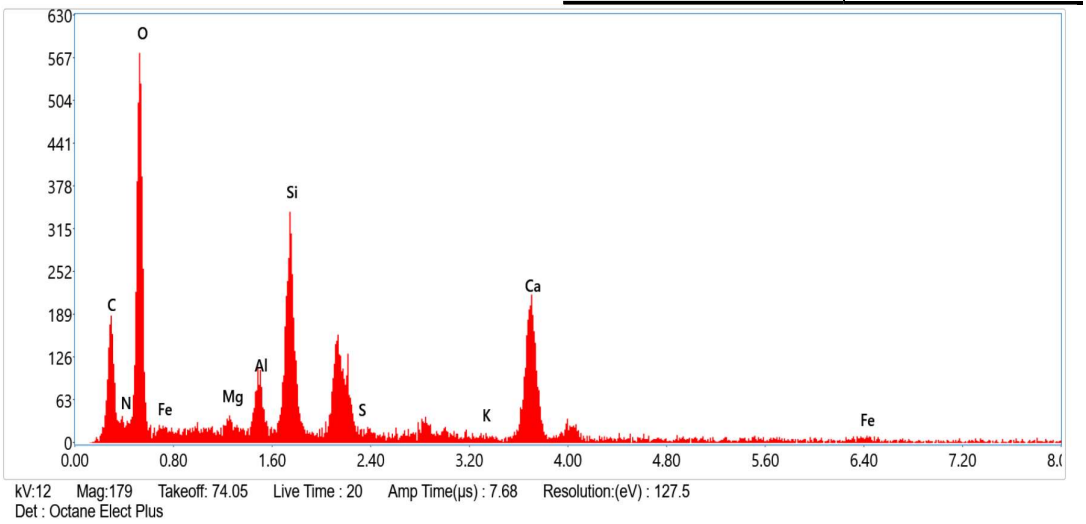

Fig. 14 Elemental analysis of SCC mix M18

It is inferred from the microstructural analysis of design mixes of SCC that due to the sphericity of the fly ash particles compared to angular cement particles, the rheology remains undeterred by the addition of fibers in the SCC. Further, it may be inferred from the microstructural analysis of SCC that there is an enhancement in bonding strength due to the mixing of fibers with the consideration that the rheology requirements of SCC remain unaffected. Visual observations from the micrographs show the best and ideal situation that can be observed for fly ash particles, which are perfectly spherical with very smooth surfaces. Besides, some level of accumulation of fibers can be anticipated even if they are dispersed well in the mix, which can influence the rheology in terms of both sphericity and angularity and strength and durability.

5.6 Numerical modelling

Predictive modeling is a process for estimating future results based on historical data using statistical or computational techniques. In the case of SCC, some of the predictive models are developed for different properties, such as compressive strength, workability, durability, and other mechanical and rheological characteristics. A prominent benefit of using predictive modeling is that the relationship between the input variables and output responses is established, without usual exhaustive experimental efforts.

The conventional method of SCC mix design is usually based on empirical relationships and iterative laboratory experimentation; it has inherent limitations in the pursuit of optimized and sustainable concrete solutions. AI will be one of the game-changing influences in this respect. AI techniques, such as Regression Analysis, Artificial Neural Networks, and Support Vector Regression, have become effective tools in predicting the properties and performance of SCC. Such methods can develop models that are capable of adequately predicting an output based on input variables, considerably reducing the need for empirical testing. This chapter further discusses the application of such AI techniques in predictive modeling for SCC with a focus on regression, ANN, and SVR.

Artificial Neural Network

The ANN was developed for the prediction of compressive strength and split tensile strength for Self-Compacting Concrete. It follows a well-structured and quite methodical approach so that accurate and reliable predictions are expected at the end. It all started with the preparation of the dataset, where the features and target variables were identified. In this case, it had two target variables: CS28 and TS28. Thus, it now becomes a regression problem with multiple outputs. In doing so, the data was split into train and test datasets to facilitate the model's performance on unseen data for evaluation, ensuring that the predictions the model makes are generalizable beyond training data. Feature scaling was done using StandardScaler to enhance neural network efficiency and convergence. This was an important step because it rescaled the input features to be similarly sized, thus making sure that all of them had equal contributions toward the learning of the model and none would have a disproportionate influence on the predictions. The performance of the trained model was tested against the predicted values on CS28 and TS28 versus the actual values of the test set as shown in the Fig. 15 and Fig. 16. Scatter plots for both target variables were created where the predicted values are plotted against the actual values. On the CS28 scatter plot, the predicted values were colored blue, while on the TS28 scatter plot, they were green. In both plots, a red diagonal line was drawn showing the ideal case that should be covered by the predictions of the real values. The closeness of the data points to this red diagonal line within the scatter plot would represent how good the predictions are, merely from the model. If the points very closely follow the red line, then the predictive capability of the model will be good; otherwise, deviations will let one know how much error is in the predictions. It is clear how intuitive these visual assessments are in showing how well the model does at predicting compressive and tensile concretizing strengths.

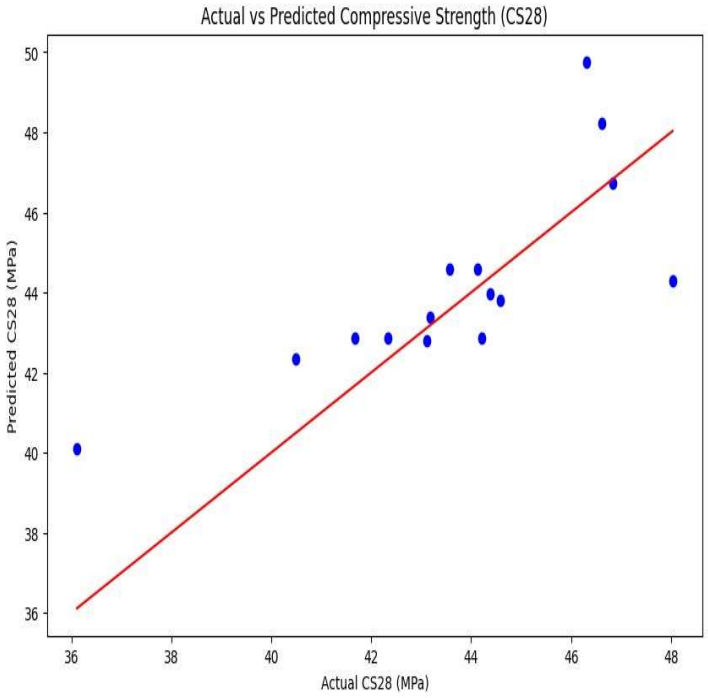

Figure 15 Actual v/s Predicted Compressive Strength using ANN

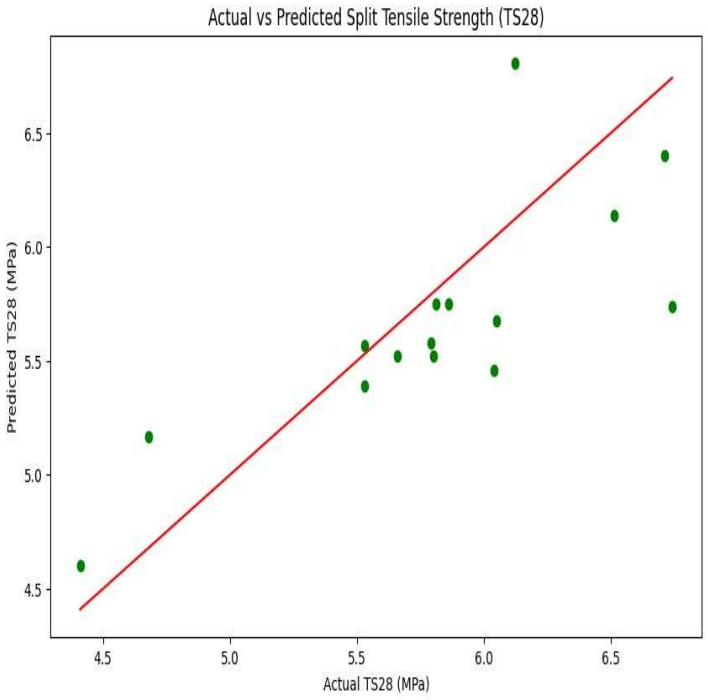

Figure 16 Actual v/s Predicted Split Tensile Strength using ANN

Support Vector Regression (SVR)

The SVR model is used with a linear kernel to carry out the tasks of predicting compressive strength and tensile strength for concrete. SVR is a variant of the Support Vector Machine, especially developed for the purpose of performing regression. Unlike traditional linear regression, SVR focuses on finding the best-fitting line (or hyperplane in multidimensional space) with a defined margin of tolerance. SVR tries to find the solution which minimizes errors and at the same time occupies the best possible space, implying the way to identify observations above or below the margin. In this SVR model, a linear kernel was employed, which would mean the algorithm was seeking a linear relationship between the input features and target variable. This would be appropriate in a context of a relationship between the two sets of variables: the independent variables, like superplasticizer, fly ash, steel fibres and polypropylene fibres, on the one hand, and the dependent variables, like the CS28 and TS28, on the other.
the plots for actual values against the predicted values using a scatter plot are drawn, illustrating the performance of the model as shown in the Fig. 17 for CS28 and Fig. 18 for TS28. A red dashed in the plot, which indicates the perfect predictions, actual values equal predicted. The better the model's predictions, the closer all the points will be to this line. It helps in visualization regarding how the model generalizes to new data and gives a feel, intuitively, about the accuracy of the model and where it might underperform. This is a nice approach that brings together two important things: evaluation metrics and visualization. This results in an effective way of evaluating the performance of an SVR model concerning prediction capability in concrete strength characteristics.

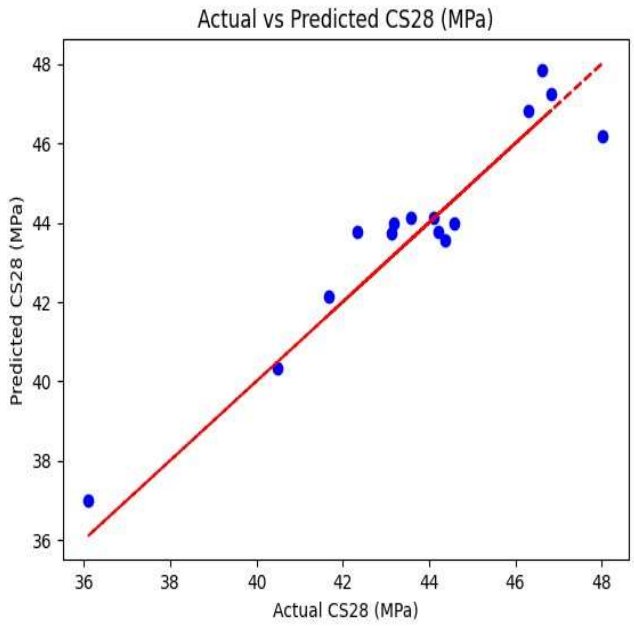

Figure 17 Actual v/s Predicted Compressive Strength using SVR

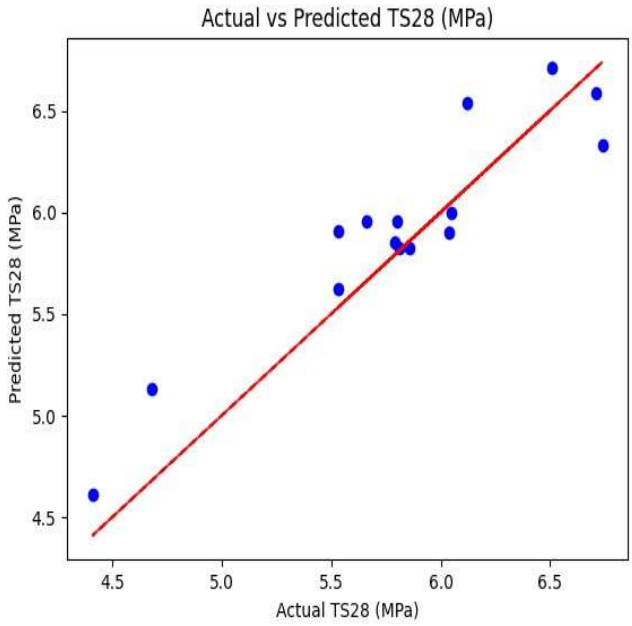

Figure 18 Actual v/s Predicted Split Tensile Strength using SVR

Eq. 1 and Eq. 2 represent the SVR model prediction equation for CS28 and TS28, respectively. The estimated compressive strength of concrete with combined effects of the superplasticizer, fly-ash, polypropylene fibres, and steel fibres in Eq.1 rests on their coefficients. In Eq.2, it estimates the tensile strength of concrete by taking the effects of the superplasticizer, fly-ash, polypropylene fibres, and steel fibres, each by their coefficients.

$$\text{CS28} = 46.12 + (1.94 * \text{SP}) + (1.42 * \text{Fly Ash}) + (0.95 * \text{PPF}) + (1.14 * \text{SF}) \quad \text{-Eq. 1}$$

$$\text{TS28} = 6.40 + (0.359 * \text{SP}) + (0.29 * \text{Fly Ash}) + (0.21 * \text{PPF}) + (0.17 * \text{SF}) \quad \text{-Eq. 2}$$

Multiple Linear Regression

In addition to the ANN, and SVR, MLR is also used to predict the CS28n and TS28 with the given independent variables, same as in previous two approaches. Here, the dataset is loaded and then creates the relevant features and target variables. After that, it is to split into train and test datasets for the model performance testing with unseen data. It will standardize the input variables, helping in improving the model's performance by making sure all features get equal contribution. A model is trained using a Linear Regression algorithm on the scaled training data, with the trained model predicting both the training and test sets. Model performance will be is evaluated based on metrics that make more sense regarding the specific task at hand, such as Mean Squared Error, Root Mean Squared Error, and R-squared values in order to get an idea about the accuracy of the prediction and the amount of variance explained by the model. Finally, scatter plots compare real versus predicted values of target variables, enabling one to assess the model prediction quality as shown in the Fig. 19 for CS28 and Fig. 20 for TS28. This ensures that the model is complete and the predictions are

reliable, and thus it serves to understand how concrete strength is affected by different features.
Using the MLR, models are developed to predict the CS28 and TS28, and the equations are given in Eq. 5.3 and Eq. 5.4 for CS28 and TS28 respectively.

CS28 = (2.04 * SP) + (3.39 * Fly Ash) + (0.93 * PPF) + (1.27 * SF) + 46.43 ---Eq. 5.3

TS28 = (0.36 * SP)+ (0.66 * Fly Ash) + (0.22 * PPF) + (0.23 * SF) + 6.38 ---Eq. 5.4

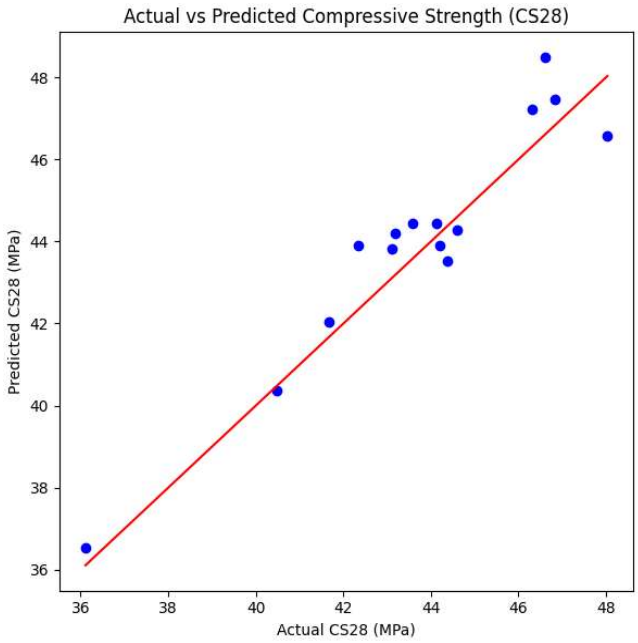

Figure 19 Actual v/s Predicted Compressive Strength using MLR

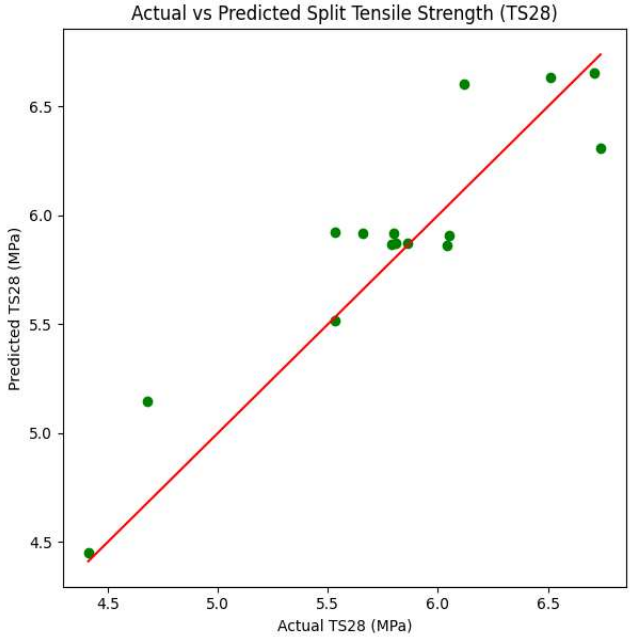

Figure 20 Actual v/s Predicted Split Tensile Strength using MLR

COMPARATIVE ANALYSIS

In the current study, three predictive models are used, ANN, SVR, and MLR. To evaluate the performance of these models some statistical/evaluation metrics like R2, RMSE, AIC, and IOA are calculated, which will enable us to conclude which one of them performs the best. Such performance studies are of prime importance in any predictive modeling for ensuring that the selected model will be most accurate and with the best reliability in predictions.

Compressive strength at 28 days (CS28)

Here, for all metrics, SVR seemed to perform the best. It returns the highest IOA, the lowest RMSE, and very good R^2 and AIC values; thus, it becomes one of the best options to make accurate and efficient predictions. MLR did well but was slightly less optimal than SVR on AIC and RMSE values. Compared to SVR and MLR, ANN has rather poor performance with lower R^2, higher RMSE, and higher AIC values. This means that it is less effective in catching underlying relationships and predicting accurately. All of this critical analysis brings into the limelight that SVR is the most balanced and effective model, while the MLR gives good performance; ANN has a set of limitations which make it less favourable in this context.

Table 10. Performance Matrix for CS28

Models	Index of Agreement (IOA)	Akaike Information Criterion (AIC)	R^2	RMSE
ANN	0.85	29.09	0.55	1.89
SVR	0.98	5.34	0.91	0.86
MLR	0.97	7.75	0.89	0.93

Tensile strength at 28 days (TS28)

Hence, SVR has both the highest IOA and the lowest AIC and RMSE among all others; thus, it is a model that provides the most accurate predictions due to its best balance of fit versus complexity. MLR also runs well, with its IOA and RMSE close to those of SVR, though the AIC is a little higher than that of SVR, thus making this model a little less optimal than SVR. The ANN approach had a lower IOA, higher AIC, and lower R^2 as compared to the rest, which means it is a less efficient way of capturing patterns in data and thus providing an accurate prediction. According to a critical analysis, SVR happened to be the most efficient and accurate model of all, followed by MLR, which is still high, though a little below the optimum level attained by SVR, and ANN with serious limitations in its predictive performance.

Table 11. Performance Matrix for TS28

Models	Index of Agreement (IOA)	Akaike Information Criterion (AIC)	R^2	RMSE
ANN	0.85	-16.06	0.54	0.42
SVR	0.95	-31.70	0.84	0.25
MLR	0.95	-31.29	0.83	0.25

6. Conclusion

This study highlights the importance of SCC and suggests advanced technological advancements in the sustainable construction industry. The crucial findings of the study indicate significant practical implications for the construction industry, showcasing the application of the formulated SCC in real-world scenarios. The study's insights into material correlations contribute to improved durability and strength characteristics, ensuring the longevity and resilience of constructed structures. In essence, the study's findings provide a practical and technically informed approach to optimizing SCC, offering benefits that address critical challenges in the construction industry. The study preliminarily emphasizes using multiple additives such as fly ash, fibers, and plasticizers in different compositions to ensure the desired outcome of SCC from a sustainability perspective. The study further used Taguchi's L18 array to design the experiments with minimalist experimental requirements for optimum results. Further, the study has performed a series of macro and micro experimental evaluations to evaluate the behavior of designed concrete in various aspects requisite for the optimum utilization of designed concrete. Moreover, the investigation of physical properties such as compressive strength, tensile strength, porosity, permeability, and durability factors have been performed to expedite the expertise of decisions regarding mix design, quality control, and the suitability of concrete for specific applications, contributing to the long-term integrity and safety of concrete structures.

A predictive model was developed and validated using multiple regression analysis to renounce the exertion of experimental analysis, and from the results and models developed. In addition to the above regression models, this study extends on the estimation of CS28 and TS28 of SCC, considering their importance for the assessment of structural integrity and long-term performance. Citing the limitation of conventionally used methods, several advanced techniques such as SVM, ANN, ANFIS-GA, and MLR were employed to develop predictive models, and the following conclusions were made during the study.

- All the mixes (M1-M18) met the EFNARC recommended values for passing ability and flowability properties, except M-2 and M-3.

- Increasing the fibers' content considerably affects the rheological properties of SCC as it negatively impacts its fresh state properties, which can be seen from the results of passing ability and flowability tests. Further, on evaluation of rheological parameters, it was observed that M16 mix having a composition of 2% superplasticizer, 145 kg fly ash, and 1 % steel fiber produced the best fresh concrete/ rheological properties with slump value of 800 mm and v-funnel time of 6 sec, thus emanating the desired properties of SCC.

- On the contrary, the worst rheological properties were observed for M3, constituting 0.5% PP fibers and steel fibers as 1 % along with the superplasticizer of 1.5 % and fly ash of 115 kg with slump value of 630 mm and V-funnel time of 14 sec, thus emancipating that presence of fibers leads to diminution of desired properties of SCC.

- The results further indicate that the mechanical properties and durability properties are enhanced by incorporating the fibers. It was observed that the M18 mix constituting 0.5% of PP fibers and steel fibers each, 2% superplasticizer, and 145 kg fly ash demonstrated superior performance wherein it was observed that the mix had the highest compressive strength of 57.2 MPa, split tensile strength of 7.8 MPa and utmost durability properties were observed along with the requirement of rheological properties within the acceptable limits.

Henceforth, based on the rheology, mechanical properties, and durability criteria, the M18 mix was recommended for using SCC.

- The microstructural examination reveals critical details such as air voids, un-hydrated cement particles, and potential undesirable reactions thus aiding in optimizing mix design and ensuring homogeneity post-hardening. Beyond quality control during production, microstructural analysis is pivotal tool for understanding how additives influence the microstructural composition that is crucial for unravelling the material's full potential.

- It was also verified from the predictive models that fiber content is positively related to the mechanical properties of SCC. Also, it is seen that on increasing the content of the admixtures (mineral plus chemical), mechanical properties have improved a lot.

- Predictive models such as SVR, ANN, and MLR were assessed against their performance by incorporating statistical metrics: IOA, AIC, coefficient of determination (R^2), and RMSE. These metrics have been used for comparing accuracy, efficiency, and reliability in each model while predicting the properties of SCC.

- The SVR and MLR depicted excellent performances in the prediction of TS28, with the same IOA value of 0.95, a very high value of R^2, which is 0.84 for each model, respectively, and with the minimum RMSE value, reaching 0.25 for both models. This testifies to the fact that SVR and MLR serve equally well for making predictions about TS28, although SVR is considered more suitable attributed to the trade-off between model fit and model complexity being better. On the contrary, ANN performances are lower, with IOA of 0.85 and a lower R^2 of 0.54 and higher RMSE of 0.42, reflecting the bounded nature of predictive accuracy for the TS28. In general, SVR proved to be the best model for both CS28 and TS28 predictions due to its best accuracy and lowest prediction errors among the three methods and ANN proved to be the least favourable because of substantial predictive limitations, though.

7. Future Scope

In paving the way for future research, current study illustrates several promising directions that can further advance our understanding of SCC and optimize its practical application in the construction industry; some of them are as follows:

- There is room for exploring alternative additives or admixtures that may further improve SCC characteristics while considering the environmental sustainability of these materials.
- Exploring the impact of varying environmental conditions and material compositions on SCC performance that could refine our predictive models and enhance the precision of mix designs.
- The identified correlations between durability, strength, and rheological parameters open avenues for in-depth investigations into the underlying mechanisms influencing these relationships.
- Optimizing and fine-tuning the existing predictive models, especially the SVM, ANN, and ANFIS-GA models, to achieve even higher accuracy in estimating compressive and tensile strengths over a wide variety of mixed designs.
- Extend to a broader range of parameters influencing the properties of SCC, such as curing conditions, type and content of supplementary cementitious materials, and environmental conditions, to develop comprehensive predictive models.
- Exploration of the application of predictive models to estimate dynamic properties of SCC and understanding the long-term performance and durability for the practical implementation of SCC in construction projects.

8. Publications

International Journals

- Agrawal, A., Chandak, N.R. Predictive modeling of rheological, mechanical and durability characteristics of hybrid fiber-reinforced self-compacting concrete. *Innov. Infrastruct. Solut.* 9, 131 (2024). https://doi.org/10.1007/s41062-024-01444-2 **(Scopus Indexed)**

- Agrawal, A., Chandak, N., (2024). Advanced AI Tools for Predicting Mechanical Properties of Self-Compacting Concrete. Architecture Civil Engineering Environment, **(Web of Science Indexed, Article in press)**

International Conferences

- Agrawal, A., Chandak, N. (2022). Deep Insights into the Self-compacting Concrete with Hybrid Fibers. In: Ha-Minh, C., Tang, A.M., Bui, T.Q., Vu, X.H., Huynh, D.V.K. (eds) CIGOS 2021, Emerging Technologies and Applications for Green Infrastructure. Lecture Notes in Civil Engineering, vol 203. Springer, Singapore. https://doi.org/10.1007/978-981-16-7160-9_127 (Presented and Published) (**Scopus Indexed**)

- Raj, R., Bhat, M., Agrawal, A., Chandak, N. (2022). Review on the Durability Parameters of Self-compacting Concrete. In: Gupta, A.K., Shukla, S.K., Azamathulla, H. (eds) Advances in Construction Materials and Sustainable Environment. Lecture Notes in Civil Engineering, vol 196. Springer, Singapore. https://doi.org/10.1007/978-981-16-6557-8_18 (Presented and Published) (**Scopus Indexed**)

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